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Detection of Anomalies in Environmental Gamma Radiation Background with Hopfield Artificial Neural Network

Consortium on Nuclear Security Technologies (CONNECT) Q3 Report

Nuclear Science and Engineering Division

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Consortium on Nuclear Security Technologies (CONNECT) Q3 Report

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Abstract

Environmental screening of gamma radiation consists of detecting weak nuisance and anomaly signal in the presence of strong and highly varying background. In a typical scenario, a mobile detector-spectrometer continuously measures gamma radiation spectra in short, e.g., one-second, signal acquisition intervals. The measurement data is a 2D matrix, where one dimension is gamma ray energy, and the other dimension is the number of measurements or total time. In principle, gamma radiation sources can be detected and identified from the measured data by their unique spectral lines. Detecting sources from data measured in a search scenario is difficult due to the highly varying background because of naturally occurring radioactive material (NORM), and low signal-to-noise ratio (S/N) of spectral signal measured during one-second acquisition intervals. The objective of this work is to investigate performance of a Hopfield Neural Network (HNN) in in detection and identification of weak nuisances and anomalies events in the presence of a highly fluctuating background. Performance of HNN algorithm is benchmarked using search data from an environmental screening campaign. One data set contained a ^{137}Cs source, and another dataset contained a ^{131}I source.

1. Introduction

Environmental screening of gamma radiation consists of detecting weak nuisance and anomaly signal in the presence of strong and highly varying background. In a typical scenario, a mobile detector-spectrometer continuously measures gamma radiation spectra in short, e.g., one-second, signal acquisition intervals. The measurement data is a 2D matrix, where one dimension is gamma ray energy, and the other dimension is the number of measurements or total time. In principle, gamma radiation sources can be detected and identified from the measured data by their unique spectral lines. Detecting sources from data measured in a search scenario is difficult due to the highly varying background because of naturally occurring radioactive material (NORM), and low signal-to-noise ratio (S/N) of spectral signal measured during one-second acquisition intervals.. As an example, Figure 1 shows images of gamma counts obtained with NaI detectors placed on a mobile platform in a drive through portions of the city of Chicago. Gamma counts per second (CPS), which are integrated over the energy spectrum, are displayed on the city map with pseudo color. Brighter counts indicate larger number of total counts. As seen in the figure, there is significant fluctuation of gamma counts due to NORM in an urban setting.

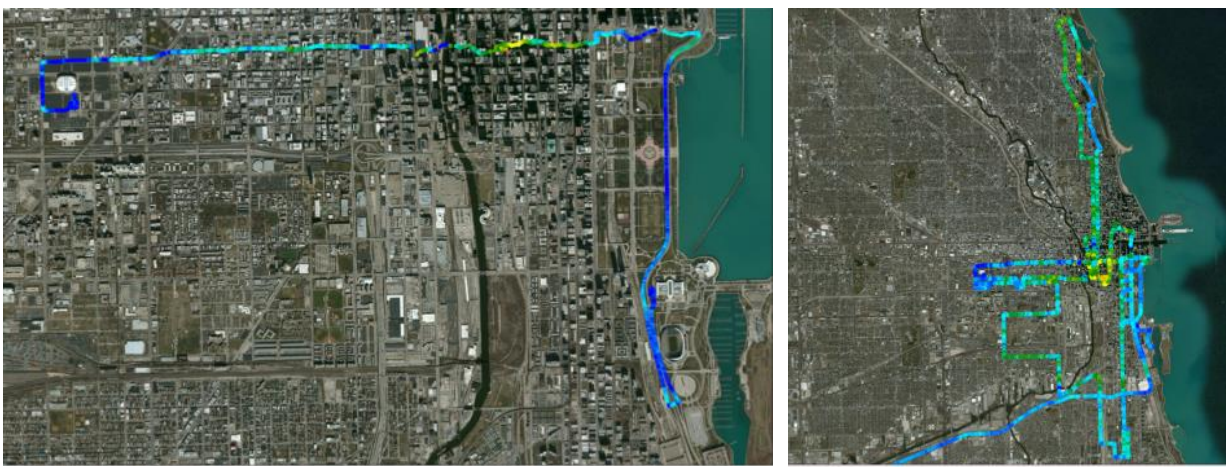

Figure 1 – Gamma counts, measured while driving with NaI detector through sections of the city of Chicago, displayed with pseudo color. Brighter colors indicate larger number of total counts.

In this work, we develop a Hopfield Artificial Neural Networks (HANN) to detect a weak signal anomaly hidden among the highly fluctuating background spectra. HANN is an Associative Memory algorithm inspired by the ability of a human brain to recognize objects from memory of past observations. The anomaly is the unstable orphan isotope that appears in the natural background consisting from gamma radiation by primordial isotopes. As part of HNN data analysis, the measurement 2D matrix is converted into an image, where the intensity of each pixel is given by counts per second (CPS). HNN is trained on segments of the image containing labeled anomalies and background only measurements. Performance of HNN is benchmarked using search data from an environmental screening campaign with NaI(Tl) detector-spectrometer with 1024 spectral channels and energy bandwidth from 0 to 3000keV. One data set with 4265 one-second measurements contains a ^{137}Cs source, and another dataset with 5827 one-second measurements contains a ^{131}I source. Performance metrics of HANN include accuracy of detection and algorithm run time.

2. Hopfield Artificial Neural Networks for Anomaly Detection

2.1. Hopfield Artificial Neural Network (HANN) Description

HANN is an associative memory algorithm inspired by human brain ability to learn from observations. The brain consists of neurons transmitting signals through the nervous system. The transmitting part of neurons are axons, which are long thin structures in which action potentials are generated. The receiving part of a neuron is a dendrite, which receives synaptic inputs from axons. The total sum of dendritic inputs determines if the neuron will fire an action potential [4]. HANN is a recurrent artificial neural network and a type of spin glass or Ising model, which provides model for understanding human memory [4]. HANN contains artificial neurons, which are binary threshold units, with the values of the states depending on unit's input exceeding its threshold. The interactions between neurons take values of 1 or -1 synaptic weights. Information is delivered to the next neuron that can be an output neuron or a process neuron. HANN implements an auto-associative memory by interconnecting each artificial neuron with all others, but not with themselves. The interactions of HANN neuron's are learned through Hebbian law of association [4], which provides a method to model memory for image reconstruction and pattern recognition. The weight matrix W matrix, calculated in Equation (1), is the sum of each independent weight of each neuron. Here x represents the training mode of the input vector.

$$W = \sum_i^N x_i * x_i^T \tag{1}$$

Discrete HNN has two ways to update and retrieve a memory pattern. The first one is asynchronous, which consists of updating one neuron at time until the system converges to a desire output. This is a very efficient method when the memory storage requires several samples to be memorized, but slows down the processing time of the system. The second one is synchronous, in which all neurons fire at once. Updating the system, we repeat the process several times until system converges to the desired output. Equation 2 describes these processes, where Y is the output, x is the input, and ξ represents a distorted input.

$$Y = sgn(W * \xi^T) \tag{2}$$

The weight matrix contains the memory patterns, which is used to retrieve the desire data by inputting the test data and iterate the neural network from state to state until it retrieves the correct pattern. This response is accomplish by the feedback characteristic of the system that allows the output to correct itself by iteration through the system until convergence. The diagram of a HANN is depicted in Figure 1.

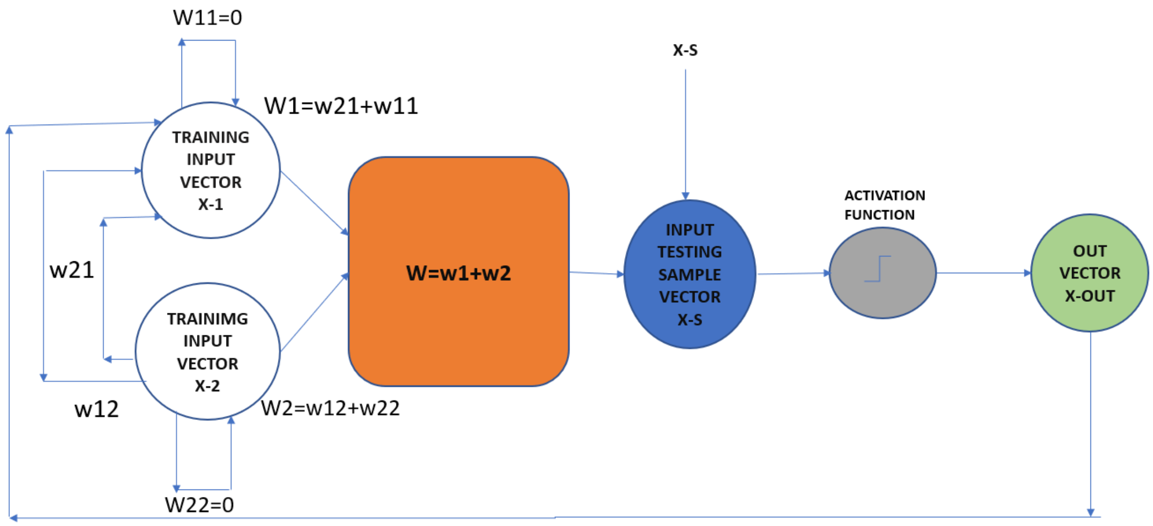

Figure 2 – Hopfield Artificial Neural Network structure

2.2. Image Processing Algorithm for Gamma Spectroscopy in Search Survey

Interactions between HANN neurons have units that take on values [1,-1]. To use HANN on a data set requires conversion of data to binary threshold HANN units. This is accomplished by converting original data into a grayscale intensity image, thresholding and normalizing the data to the set of binary values [1,0], and then converting the zero values to -1's. This process is illustrated in Figures 3 and 4. An example of grayscale intensity image of counts per second (CPS) for various energies and times is shown in Figure 3. The data set consists of 5827 one-second measurements of gamma spectra with NaI(Tl) detector-spectrometer with 1024 spectral channels and energy bandwidth from 0 to 3000keV. Grayscale intensity image of CPS is plotted with MATLAB.

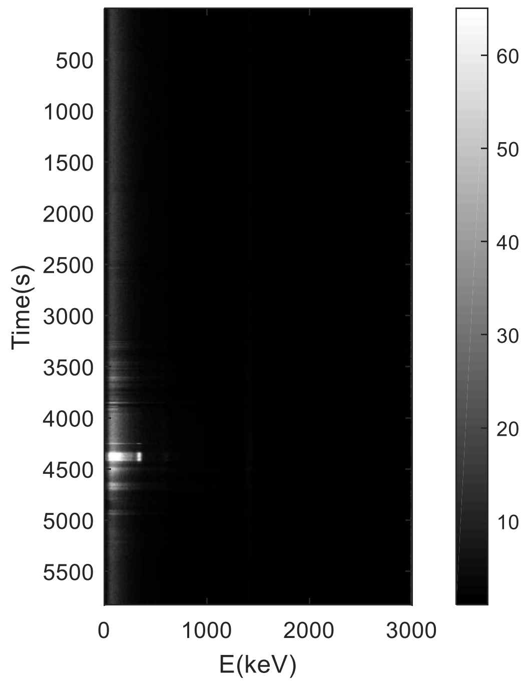

Figure 3 – Grayscale image of gamma counts per second (CPS)

As shown in the flow chart in Figure 4, the grayscale intensity data matrix of Figure 3 is thresholded and normalized to obtain binary representation [1 0], which are next converted to HANN units set [1 -1].

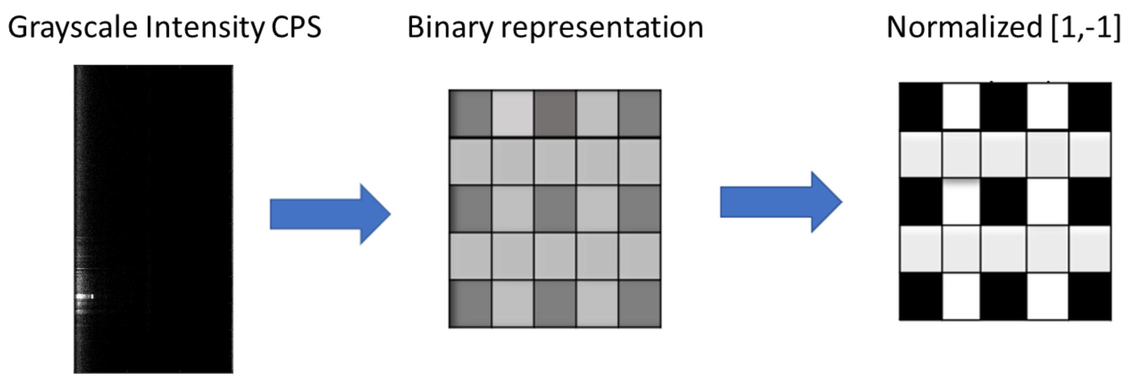

Figure 4 – Flow chart of conversion of grayscale CPS image into matrix of HANN normalized values

In the process shown in Figure 5, sets of anomaly and background-only measurements are sampled for training HANN. The input x is a 1024-element vector of gamma spectrum measured in one second.

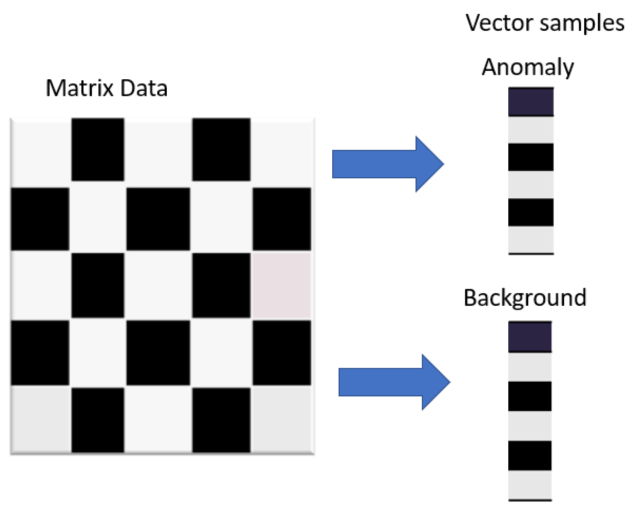

Figure 5 – HANN training process

3. Detection of Orphan Sources in Gamma Background Screening Data with HANN

Performance of HANN algorithm was benchmarked in detection of orphan sources in data sets containing measurements of ^{137}Cs and ^{131}I isotopes, respectively. The first dataset contained 4265 one-second spectra from a NaI scintillation detector, including 95 one-second spectra of ^{137}Cs source. The second dataset contained 5827 one-second spectra from a NaI scintillation detector, including 88 one-second spectra of ^{131}I source. Both datasets contained 1024 channels ranging from 0 to 3000keV.

HANN models were created using MATLAB Deep Learning Toolbox software. Training of HANN was accomplished by taking measurements of labeled source and background-only subsets. Once HANN training is completed, each one-second second vector of gamma counts from the data set is submitted as a query to HANN image spectrum data matrix to detect if it belongs to an anomaly or background, Even if the energy peaks of the anomaly spectrum are convoluted by the background, HANN is expected to reconstruct the pattern. Flow chart of HANN anomaly detection is shown in Figure 6.

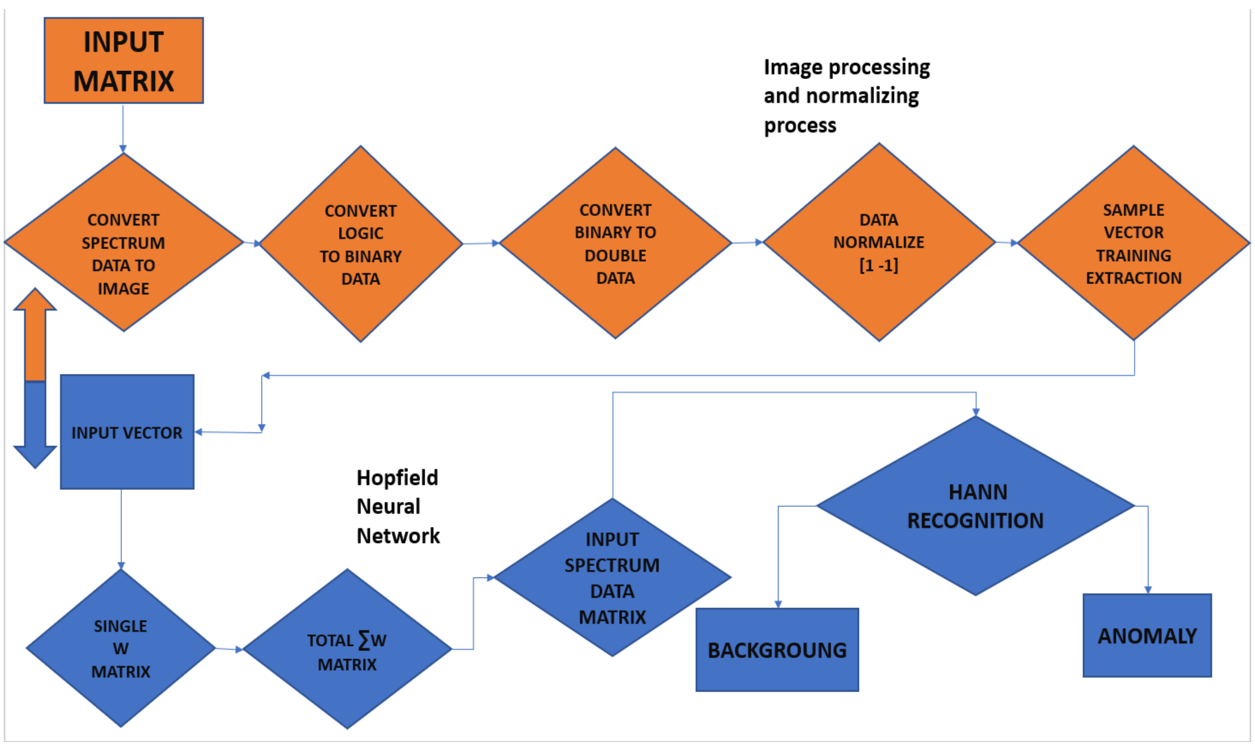

Figure 6 – HANN anomaly detection flow chart

Performance of HANN was evaluated using precision, recall, and F_1 score metrics, which were calculated with the following equations:

$$Precision = \frac{tp}{tp + fp} \tag{3}$$

$$Recall = \frac{tp}{tp + fn} \tag{4}$$

$$F_1 = 2 * \frac{precision * recall}{precision + recall} \tag{5}$$

where t_p is true positives, f_p is false positives, and f_n is false negatives. For K-means clustering, due to the varying centroids, we took an average of the precision and recall between ten trials, which we then used to create the average F_1 score

Table 1 and 2 show the calculated precision, recall, and F_1 score for the dataset containing ^{137}Cs and ^{131}I sources, respectively.

Table 1 – Precision, Recall and F_1 score for ^{137}Cs source detection

Samples	95
Number of Trials	10
Predicted	83-97
Precision	88.2%
Recall	89.8%
F_1 score	**89%**

Table 2 – Precision, Recall and F_1 score for ^{131}I source detection

Samples	88
Number of Trials	10
Predicated	97-99
Precision	93.5%
Recall	97.7%
F_1 score	**95.5%**

Table 3 lists values for overall HANN accuracy for the analyzing two data sets. These metrics are similar to those of the prior work on unsupervised learning of the same data sets with K-means and SOM clustering [5].

Table 3 – Benchmarking of HANN algorithm performance

Data Set	**Accuracy (%)**	**Run time (s)**
^{137}Cs	88	5.1
^{131}I	9	7.5

4. Conclusions

We have developed a Hopfield Artificial Neural Networks (HANN) to detect a weak signal anomaly hidden among the highly fluctuating background spectra. HANN is an associative memory algorithm inspired by the ability of a human brain to recognize objects from memory of past observations. The anomaly is the unstable orphan isotope that appears in the natural background consisting from gamma radiation by primordial isotopes. As part of HNN data analysis, the measurement 2D matrix is converted into an image, where the intensity of each pixel is given by counts per second (CPS). HNN is trained on segments of the image containing labeled anomalies and background only measurements. Performance of HNN is benchmarked using search data from an environmental screening campaign with NaI(Tl) detector-spectrometer with 1024 spectral channels and energy bandwidth from 0 to 3000keV. One data set with 4265 one-second measurements contains a ^{137}Cs source, and another dataset with 5827 one-second measurements contains a ^{131}I source. Performance metrics of HANN include accuracy of detection and algorithm run time. The result obtains by the HANN are 88% accuracy for ^{137}Cs with runtime of 5.1s and 95% accuracy for ^{131}I with runtime of 7.5s. These performance metrics are similar to those of unsupervised learning using K-means and SOM clustering. Future work will explore performance of Quantum Hopfield Networks.

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